AUTOREGRESSIVE MODEL LEARNING DEVICE FOR TIME-SERIES DATA AND A DEVICE TO DETECT OUTLIER AND CHANGE POINT USING THE SAME

BACKGROUNDS OF THE INVENTION

1. Field of the Invention

The present invention relates to an autoregressive model learning device for time-series data and a device to detect outlier and change point using the same and particularly relates to a detection device associated with data analysis and data mining technologies that calculates the outlier score and the change point score for the data described with the discrete variate and/or continuous variate sequentially input, so as to detect the outlier and the change point with a high accuracy.

2. Description of the Related Art

Conventionally, this type of detection device that calculates the outlier score and the change point score of the time-series data for detection of the outlier and the change point uses the technologies treated in the fields of statistics, machine learning, data mining and others. In other words, abnormal value detection and change point detection, which are the functions to be realized by the present invention, have been conventionally addressed by the fields of statistics, machine learning, data mining and so on.

The present invention, however, is applied to the situation where the stationarity is not assumed for the data generation source or the information source.

Literature on the outlier detection in such a case includes the materials as shown below:

One example is a method by P. Burge and J. Shawe-Taylor called "Detecting cellular fraud using adaptive prototypes" (Proceedings of AI Approaches to Fraud Detection and Risk Management,pp:9-13,1997).

Another example is a method by K. Yamanishi titles "On-line Unsupervised Outlier Detection Using Finite Mixtures with Discounting Learning Algorithms (Proc. of the Sixth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ACM Press,pp:320-324,2000).

Still another example is a method by U. Murad and G. Pinkas called "Unsupervised profiling for identifying superimposed fraud"(Proceedings of 3rd European Conference on Principles and Practice of Knowledge Discovery in Databases,pp:251-261,1999).

These materials use the adaptive outlier detection algorithm to handle the non-stationarity.

Further, according to a known ordinary method to detect the change point in statistics, the number of change points in the given data is decided in advance and a model is applied considering that the data among change points can be described by a stationary model.

Such a method is described, for example, in the following literature.

An example is a paper by B. Guthery titled "Partition regression" in Journal of American Statistical Association](69:945--947,1974) or a paper by M. Huskova "Nonparametric procedures for detecting a change in simple linear regression models" in the book titled "Applied Change Point Problems in Statistics" (Nova Science Publishers,Inc,1995).

For detection of the change point in data mining, a method by V. Guralnik and J. Srivastava is described in "Event detection from time series data" (Proc.of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ACM Press,pp:32-42,1999).

The conventional methods and devices according to the above literature have drawbacks as follows as a device to detect outliers and change points from the time-series data.

In the outlier detection method that can be sequentially processed by the conventional machine learning technology such as the method by P. Burge and J. Shawe-Taylor, the method by K. Yamanishi et al., or the method by U. Murad and G. Pinkas as described above, any statistic model suitable for time-series data is not used. Therefore, there is a drawback that the characteristics of the data having time-series nature cannot be grasped sufficiently. The statistic model

suitable for time-series data here means a model that can express correlation among data at different timings. For example, the autoregressive model and Markov model are such type of models.

In addition, the conventional change point detection method described in the paper by V. Guralnik and J. Srivastava basically uses collective processing of data or so-called batch processing and cannot process the data sequentially. Further, the conventional change point detection methods as described above are designed on the assumption that the data are locally stationary, but such assumption is not appropriate in the reality and should be removed.

Further, though it is preferable to handle the outliers and the change points together and detect each of them in application of data mining or the like, schemes to handle them together only has been known so far.

SUMMARY OF THE INVENTION

An object of the present invention is to solve the above problems. More specifically, it is an object of the present invention to use a statistic model that can grasp the nature of the time-series data, to support non-stationary data, to handle the outliers and the change points together and to sequentially execute the processing.

According to the first aspect of the invention, an autoregressive model learning device that sequentially reads the data string of the real number vector values and learns the probability distribution for generation of the data string using the autoregressive model comprises

a data updating device that updates the sufficient statistic of the autoregressive model with forgetting the past data using newly read data and a parameter calculator that reads the sufficient statistic updated by the data updating device and calculates the parameter of the autoregressive model using the sufficient statistic.

According to the second aspect of the invention, an outlier and change point detection device that calculates the outlier score and the change point score for the data described with the sequentially input discrete variate and/or continuous variate so as to detect the outlier and the change point comprises

a first model learning device that learns the generation mechanism for the read data series as the time-series statistic model specified by the finite number of parameters, and

an outlier score calculator that reads the value of the parameters obtained through learning by the first model learning device, calculates the outlier score of the data based on the read parameter of the time-series

model and the input data and outputs the results.

In the preferred construction, the outlier and change point detection device further comprises

as a detection device to detect the change point,

a moving average calculator that sequentially reads the outlier scores calculated by the outlier score calculator and calculates their moving average,

a second model learning device that sequentially reads the moving average of the outlier scores calculated by the moving average calculator and learns the generation mechanism for the moving average series in the read score as a time-series statistic model specified by the finite number of parameters, and

a change point score calculator that reads the parameter value obtained by learning by the second model learning device and calculates the outlier score for each moving average based on the read parameter of the time-series model and the moving average of the input outlier scores and outputs the outlier score for each moving average as the change point score of the original data.

In another preferred construction, the first model learning device learns, in case the sequentially input data are described with continuous variate only, the probability distribution for generation of the data string with sequentially reading the data strings of the real number vector values using the autoregressive model

and further comprises a data updating device to update the sufficient statistic of the autoregressive model with forgetting the past data using the newly read data and a parameter calculator to read the sufficient statistic updated by the data updating device and to calculate the parameter of the autoregressive model using the sufficient statistic.

In another preferred construction, the outlier score calculator and the change point score calculator are considered as a single score calculator, further comprising as a device to determine the candidates of outliers and change points in the series for the data series described in discrete and/or continuous variates, a sort device to sort the data in descending order based on the outlier score and the change point score calculated by the score calculator and the display device that displays the data with higher scores according to the order sorted by the sort device as the candidates of outliers and change points.

In another preferred construction, the outlier score calculator and the change point score calculator are considered as a single score calculator, further comprising, as a device to determine candidates of outliers and change points in the series for the data described in discrete and/or continuous variates sequentially input, a score judgement device that outputs the data over the predetermined threshold from

the outlier score and the change point score calculated by the score calculator as the candidates of outliers or change points.

According to the third aspect of the invention, an autoregressive model learning method in which the data string of the real number vector values are sequentially read and the probability distribution for generation of the data string is learned using the autoregressive model, comprising the steps of

a data updating step of updating the sufficient statistic of the autoregressive model with forgetting the past data using newly read data, and

a parameter calculation step of reading the sufficient statistic updated by the data updating step and calculating the parameter of the autoregressive model using the sufficient statistic.

According to another aspect of the invention, an outlier and change point detection method to detect the outlier and change point by calculating the outlier score and the change point score for the data described with the sequentially input discrete variate and/or continuous variate, comprising the steps of

a learning step of learning the mechanism to generate the read data series as a time-series statistic model specified by the finite number of parameters, and

an outlier score calculation step of reading the parameter value obtained through learning by the

learning step and calculating the outlier score of each data based on the read parameter of the time-series model and the input data and outputting the results.

In the preferred construction, the method to detect the change point further comprises a moving average calculation step of sequentially reading the outlier score calculated by the outlier score calculation step and calculating the moving average, a second learning step of sequentially reading the moving average of the outlier score calculated by the moving average calculation step and learning the generation mechanism for the moving average series in the read score as a time-series statistic model specified by the finite number of parameters, and a change point score calculation step of reading the parameter values obtained through learning by the second learning step, calculating the outlier score of each moving average based on the read parameter of the time-series model and the moving average of the input outlier scores and outputting the outlier score as the change point score of the original data.

In another preferred construction, in case the sequentially input data are described with continuous variate only, the learning step sequentially reads the data string of the real number vector values and learns the probability distribution for generation of the data string using the autoregressive model, and updates the

sufficient statistic of the autoregressive model with forgetting the past data using newly read data, reads the updated sufficient statistic and calculates the parameter of the autoregressive model using the sufficient statistic.

In another preferred construction, the outlier score calculation step and the change point score calculation step are considered as a single score calculation step and further comprises a step in which, as a method to determine candidates of outliers and change points in the series for the data series described with discrete and/or continuous variates, the data are sorted in descending order based on the calculated outlier score and the change point score and the higher score data are displayed as the outlier and change point candidates according to the order of sorting.

In another preferred construction, the outlier score calculation step and the change point score calculation step are considered as a single score calculation step and further comprising a step in which, as a method to determine outlier and change point candidates in the series, the data over the predetermined threshold selected from the calculated outlier and change point scores as the candidates of outliers or change points for the data described with discrete variate sequentially input and/or continuous

variate.

Thus, according to the present invention, the data are updated at the same time as forgetting of the past data. The present invention is suitable to process the time-series data and can improve the processing accuracy.

Other objects, features and advantages of the present invention will become clear from the detailed description given herebelow.

BRIEF DESCRIPTION OF THE DRAWINGS

the present invention will be understood more fully from the detailed description given herebelow and from the accompanying drawings of the preferred embodiment of the invention, which, however, should not be taken to be limitative to the invention, but are for explanation and understanding only.

in the drawings:

Fig. 1 is a configuration diagram to show the configuration of a first embodiment of an AR model learning device according to the present invention;

Fig. 2 is a flowchart to illustrate the operation of the first embodiment;

Fig. 3 is a configuration diagram to show the configuration of second and third embodiments of a device to calculate the outlier score and the change point score according to the present invention;

Fig. 4 is a flowchart to illustrate the operation of the second embodiment;

Fig. 5 is a flowchart to illustrate the operation of the third embodiment;

Fig. 6 is a configuration diagram to show the configuration of a fourth embodiment of the device to determine outlier and change point candidates according to the present invention;

Fig. 7 is a flowchart to illustrate the operation of the fourth embodiment;

Fig. 8 is a configuration diagram to show the configuration of a fifth embodiment of the device to determine outlier and change point candidates according to the present invention different from Fig. 3;

Fig. 9 is a flowchart to illustrate the operation of the fifth embodiment; and

Fig. 10 is a graph to show an embodiment of experiment results on the change points using the score calculator shown in Fig. 2.

DESCRIPTION OF THE PREFERRED EMBODIMENT

The preferred embodiment of the present invention will be discussed hereinafter in detail with reference to the accompanying drawings. In the following description, numerous specific details are set forth in order to provide a thorough understanding of the present invention. It will be obvious, however, to those skilled

in the art that the present invention may be practiced without these specific details. In other instance, well-known structures are not shown in detail in order to unnecessary obscure the present invention.

Referring to the attached figures, preferred embodiments of the present invention are described below.

First of all, the notation is explained. "x" represents the data of n-dimensional vector value having a real number as the component. "y" represents the data of m-dimensional vector value having a discrete value as the component. "x" and "y" are collectively expressed as "z = (x, y)". A series comprising N pieces of data is expressed as "$Z^N = Z_1, Z_2, \ldots Z_N$".

A method to calculate the "outlier score" for such a series is described below.

Firstly, consider a statistic model to generate the data z: $P(Z_i|\theta) = p(x_i, y_i|\theta)$. This represents the range where "z" moves or the probability density function defined on the range Z.

"θ" is a parameter to specify the probability density and generally consists of a discrete parameter and a continuous value parameter. As the probability density function of this type, the finite mixed Gaussian distribution or the autoregressive model (time-series model) are used if "z" comprises continuous variables, for example. In case of the time-series model, the probability density of the i-th data Z_i depends on the

series Z^{i-1} so far and the model becomes as follows: $p(z_i|z^{i-1}, \theta)$

In general, for calculation of the outlier score, the value of the parameter θ is assumed (or "learned") based on the data series. Here, the parameter is learned using the "Sequential learning method", in which the data series is sequentially read and at the same time the parameter is sequentially changed based on the read data. Suppose here that the parameter value obtained as a result of learning with reading the data to z_i to be "$\theta^{(i)}$". The outlier score for "Z_{i+1}" can be calculated using this. For example, the logarithm score S_L and Hellinger score sH can be calculated by the formulas 1 and 2 below.

$$s_L = -\log p(z_{i+1}|\theta^{(i)}) \qquad \text{(formula 1)}$$

$$s_H = d^2\left(p\left(\cdot|z^i, \theta^{(i)}\right), p\left(\cdot|z^{i-1}, \theta^{(i-1)}\right)\right) \qquad \text{(formula 2)}$$

where "d^2" is the squared Hellinger distance between two probability densities and is defined by Formula 3 below.

$$d^2(p,q) = \sum_X \int\left(\sqrt{p(x,y)} - \sqrt{q(x,y)}\right)^2 dy \qquad \text{(formula 3)}$$

Next, the AR model used in the present invention is described. The AR model is a time-series statistic

model to describe the probability distribution of the series of the n-dimensional real number vector data x_i. Firstly, the series "$\omega^N = \omega_1\omega_2 \ldots \omega_N$" is introduced as an auxiliary probability variable. This is supposed to be in the same dimension as "x" (n-dimension). Generally, the k-degree AR model can be expressed by Formula 4 below.

$$w_t = \sum \Lambda_i w_{t-i} + \varepsilon \qquad \text{(formula 4)}$$

Note that A_i (i=1, ..., k) is an n-dimensional square matrix and ε is a probability variable according to normal distribution of covariance matrix Σ with an average of "0".

Suppose now that x_i can be given using u_i as "$x_i = u_i + \mu$". If Formula 5 below is given here, the probability density function of x_t can be given by Formula 6 below.

$$x_{t-k}^{t-1} = (x_{t-1} \cdots x_{t-k}) \qquad \text{(formula 5)}$$

$$p(x_t | x_{t-k}^{t-1} : \theta) = \frac{1}{(2\pi)^{k/2} |\Sigma|^{1/2}} \exp\left(-\frac{(x_t - \xi)^T}{2} \Sigma^{-1} (x_t - \xi) \right) \qquad \text{(formula 6)}$$

however, $\xi = \sum_{i=1}^{k} \Lambda_i w_{t-1} + \mu, \theta = (\Lambda_1, \cdots, \Lambda_k, \mu, \Sigma)$

An outlier level calculator sequentially reads the data series from the beginning and, when it reads the i-th data z_i, outputs its outlier level $s_{(i)}$.

Then, referring to Fig. 1, an autoregressive model learning device as described above is explained as a first embodiment. Suppose here that the constant r to express the speed of forgetting and the degree k of the AR model are given in advance. The constant r is a value from 0 to 1. Smaller constant means quicker forgetting of the past data.

As shown in the figure, the first embodiment is a data updating device and comprises a forgetting type sufficient statistic calculator 11 to receive input x_t and a parameter calculator 12 to receive the output of the same and to send the parameter value.

The forgetting type sufficient statistic calculator 11 is a device to calculate the forgetting type sufficient statistic in the AR model. The forgetting type sufficient statistic is the sufficient statistic corrected so that the influence of older data becomes smaller. The sufficient statistic here means the n-dimensional vector μ and "k+1" pieces of n-dimensional square matrix C_j ($j = 0, 1, \ldots, k$). The forgetting type sufficient statistic calculator 11 has a function to store the past data at the timing k for the k-degree AR model.

The parameter calculator 12 calculates the value for parameter θ "= (Λ_1, ..., Λ_k, μ, Σ)" of the AR model based on the given sufficient statistic.

Referring to the flowchart of Fig. 2, the operation in the first embodiment is described. Firstly, the parameters stored in the parameter calculator 12 are initialized before data reading. Then, every time the t-th data is input, the following steps are executed.

The forgetting type sufficient statistic calculator 11 deletes the oldest data it has stored when data x_t is input (Step 201) and stores the newest data x_t instead to obtain the data string "x_t, x_{t-1}, ..., x_{t-k+1}"" (Step 202).

Using this, the forgetting type sufficient statistic calculator 11 updates the sufficient statistic "μ, C_j (j = 0, ..., k)" it keeps by the update rules expressed by Formulas 7 and 8 shown below (Step 203) and sends the obtained sufficient statistic to the parameter calculator 12 (Step 204).

$$\mu := (1-r)\mu + rx_t \qquad \text{(formula 7)}$$

$$C_j := (1-r)C_j + r(x_t - \mu)(x_{t-j} - \mu)^T \qquad \text{(formula 8)}$$

The parameter calculator 12 determines the solution of the simultaneous equations for Formula 9 below having "upper bar Λ_i" (i = 1, ..., k) as the

unknown (Step 205). Note that "$C_{-j}= C_j$".

$$C_j = \sum_{i=1}^{k} \overline{\Lambda}_i C_{j-1} \ (j=1,\cdots,k) \qquad \text{(formula 9)}$$
however $\overline{\Lambda}_j (i=1,\cdots,k)$

The parameter calculator 12 substitutes the determined solution for "Λ_i" and calculates the parameter θ using Formulas 10 and 11 below (Step 206).

Then, it outputs the obtained parameter θ "= (Λ_1, ..., Λ_k, μ, Σ)" (Step 207).

$$x_{it} := \sum_{i=1}^{k} \Lambda_i (x_{t-i} - \mu) + \mu \qquad \text{(formula 10)}$$

$$\Sigma := (1-r)\Sigma + r(x_t - z_{it})(x_t - z_{it})^T \qquad \text{(formula 11)}$$

Then, referring to Fig. 3, second and third embodiments are described below.

As shown in the figure, these embodiments comprise a time series model learning devices 21 and 24 corresponding to the first and second model learning devices as described above, a moving average calculator 22 and a score calculator 23 containing both of the outlier score calculator and the change point score calculator described above. The second embodiment is realized by the time-series model learning device 21 and

an outlier score calculator and the third embodiment is realized by the time-series model learning devices 21 and 24 and the score calculator 23.

The time-series model learning devices 21 and 24 are devices to learn the parameter in the probability density function of the time series model with sequentially reading data.

Note that, on one hand, the time-series model learning device 21 is a device to learn the probability density function related to the input data z_t and the probability density function F_p used here is expressed by Formula 12 below.

$$F_p = p(z_t \mid z^{t-1}, \xi) \qquad \text{(formula 12)}$$

On the other hand, the other time-series model learning device 24 is a device to learn the probability density function related to the moving average series of the score calculated by the moving average calculator 23 and uses a k-degree AR model with a single variate. The probability density function F_{qk} is expressed by Formula 13 below.

$$F_{qk} = q(\alpha_t \mid \alpha_{t-k}^{t-1}, \theta) \qquad \text{(formula 13)}$$

The score calculator 23 reads the parameters and data of the probability density functions F_p and F_{qk} and

calculates the score for data x_t. The score calculator 23 has, in addition to its calculation function, a function to save the latest u (z) pieces of data for "Z_t" series, the latest u (α) pieces of data for "α_t" series and the previous parameter for "θ" and "ξ". In case of the probability density function F_{qk} using the k-degree AR model, for example, the logarithm score or the Hellinger score can be calculated under the condition "u(α) = k".

The moving average calculator 22 is a device that calculates and outputs the T moving average of the real number data input sequentially. For this purpose, the moving average calculator 22 has a function to store T pieces of real numbers inside.

The device related to the second embodiment works according to the order below. Referring to the flowchart of Fig. 4, the operation of the second embodiment is described below.

The entire system is initialized first. Some predetermined values are set to the devices to store the parameters and data. The device shown in the figure works as follows every time the t-th data z_t"=(x_t, y_t)" is input.

The time-series model learning device 21 and the score calculator 23 receive the input of data z_t (Step 401).

The score calculator 23 calculates the score for

data z_t as the outlier score s_t based on the parameter ξ of the probability density function F_p input and saved in the past, the input data z_t and the past data "z_{t-1}, z_{t-2}, ..., z_{t-u}" (Step 402).

Then, the obtained outlier score s_t is sent to the moving average calculator 22 and at the same time output to outside (Step 403).

The device related to the third embodiment works according to the order below following the second embodiment above. The operation of the third embodiment is described below with referring to the flowchart of Fig. 5.

When the moving average calculator 22 receives the score s_t from the score calculator 23 (Step 501), it erases the oldest saved score and saves the newly input score s_t (Step 502).

Then, the moving average calculator 22 calculates the average α_t of T pieces of saved scores and sends it to the time-series model learning device 24 (Step 503).

The time-series model learning device 24 works as explained in the first embodiment above and updates the parameter ξ of the probability density function F_{qk} using k-degree AR model with a single variate (Step 504) and sends the obtained parameter θ and the score α_t to the score calculator 23 (Step 505).

The score calculator 23 calculates the score of the score α_t or the change point score based on the

parameter θ of the probability density function F_q expressed by Formula 14 below input in the past and saved, the input data α_t and the past data "α_{t-1}, α_{t-2}, ..., α_{t-u}" (Step 506) and outputs the obtained score (Step 507).

$$F_q = q(\alpha_t \mid \alpha^{t-1}, \theta) \qquad \text{(formula 14)}$$

Then, referring to Fig. 6, a fourth embodiment is described below.

This figure shows data 31, an outlier score/change point score calculator 32, which is the score calculator described above, a scored data 33, a sort device 34 and a display device 35. The data 31 is a database storing data series with a finite length. The outlier score/change point score calculator 32 is a device to calculate the outlier score and the change point score as described in the embodiment 2 or 3 above. The scored data 33 receives and stores the outputs from the outlier score/change point score calculator 32. The sort device 34 sorts the data in the descending order of score using the outlier score and the change point score.

The devices shown in the figure work according to the order below. The operation of the fourth embodiment is described below with referring to the flowchart of Fig. 7.

The outlier score/change point score calculator

32 accesses the data 31, sequentially reads the data series and calculates the outlier score and the change point score for each data (Step 701) and then sends a three-element set of the data, the outlier score and the change point score to the scored data 33 (Step 702).

The scored data 33 stores the sent data (Step 703).

The sort device 34 accesses the database of the scored data 33 and sorts the data stored there in the descending order of score using the outlier score and the change point score and send them to the display device 35 (Step 704).

The display device 35 lists and displays two types of sorted data sent according to the sort order (Step 705).

Next, referring to Fig. 8, a fifth embodiment is described.

The figure shows data 41, an outlier score/change point score calculator 42, which is the score calculator as described above, scored data 43, a score judgement device 44 and a display device 45. The score judgement device 44 is provided in Fig. 4 instead of the sort device 34 in Fig. 3.

The data 41 is a database storing data series with a finite length. The outlier score/change point score calculator 42 is a device to calculate the outlier score and the change point score as described in the

embodiments 2 or 3 above. The scored data 43 receives and stores the outputs from the outlier score/change point score calculator 42. The score judgement device 44 accesses the database of the scored data 43 and sends the data over the predetermined threshold selected from the stored data using the outlier score and the change point score to the display device 45.

The devices shown in the figure work according to the following order. The operation of a fifth embodiment is described below with referring to the flowchart of Fig. 9.

The outlier score/change point score calculator 42 accesses the database of the data 41 and, with reading the data series sequentially, calculates the outlier score and the change point score for each data (Step 901).

To the database of the scored data 43, a three-element set consisting of the data, the outlier score and the change point score is sent sequentially (Step 902).

The database of the block 43 stores the sent data (Step 903).

The score judgement device 44 accesses the database of the scored data 43 and sends the data over the predetermined threshold selected from the stored data using the outlier score and the change point score to the display device 45 (Step 904).

The display device 45 displays the two types of sent data as they are or lists them according to the sort order (Step 905).

Next, referring to Fig. 10, the actual data analyzed using the score calculator for the outlier score and the change point score described with referring to Fig. 2 are described.

This experiment was conducted in order to find out the change point. This is an example in which the daily data of Tokyo Stock Price Index (TOPIX) (1946-1998) are analyzed and the results of the period from 1985 to 1995 are shown. The graph shows the original data and the change point score attached to them. The data are pre-processed. In other words, if the original series is "One-dimensional" and is "x_t", this is converted to "x_t, x_t-x_{t-1}". It is expected that such conversion helps detection of sharp change of the trend in addition to change of the average. According to this analysis result, it is understood that the change point score is high for so-called Black Monday and in the period of generation and collapse of the bubble economy. The graph shows a quite high peak on the day following the Black Monday.

Though the above explanation refers to the functional blocks shown in the figures, the functions can be freely distributed by separation or unification as far as the above functions are satisfied. The above

explanation does not limit the present invention.

As described above, the present invention has an effect that the extent of statistical outlier or change point appearing in the time-series data is measured and presented as the outlier score or the change point score and that their detection is enabled with a high accuracy.

The reasons are as follows:

First of all, the time-series model learning device that learns the generation mechanism of the read data series as the time-series statistic model is used for the data string input sequentially.

In addition, the score calculator calculates the outlier score of each data based on the time-series model parameter and the input data.

Further, the outlier and the change point are detected through calculation of the outlier score and the change point score by combining the moving average calculator to calculate the moving average of the outlier scores, the time-series model learning device to learn the mechanism for generation of moving average series as the time-series statistical model and a score calculator that further calculates the outlier score of the moving average based on the moving average of the outlier scores and outputs the result as the change point score of the original data.

Although the invention has been illustrated and described with respect to exemplary embodiment thereof,

it should be understood by those skilled in the art that the foregoing and various other changes, omissions and additions may be made therein and thereto, without departing from the spirit and scope of the present invention. Therefore, the present invention should not be understood as limited to the specific embodiment set out above but to include all possible embodiments which can be embodies within a scope encompassed and equivalents thereof with respect to the feature set out in the appended claims.